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MODELING RISK PRIORITIZATION OF A MANUFACTURING SUPPLY CHAIN USING DISCRETE EVENT SIMULATION

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ABSTRACT

Supply chains face a myriad of adverse risks that impact their daily operations and make them vulnerable. In addition, supply chains continue to grow in size and complexity which further sophisticates the problem. Lack of a structured approach and limitations in existing risk management methods contribute towards effective mitigation strategies not being properly developed. In this paper, we develop a discrete event simulation modelling approach to quantify the performance and risk assessment of a manufacturing supply chain in Sweden which is under the impact of risks. This approach could support decision makers by prioritizing risks according to their performance impact and facilitating the development of mitigation strategies to enhance the resilience of the supply chain. The conceptual digital model can also be used to generate synthetic data to build an artificial intelligence-enhanced predictive demonstrator model to showcase capabilities for building data-driven resilience of the supply chain.

1 INTRODUCTION

Supply chains (SCs) are prone to several external and internal risks and disruptions which unfortunately cannot be avoided. SC risks are those that impact its value-creating outcomes in terms of productivity, volume and quality of products produced from a geographical and time-dependent perspective (Bogataj and Bogataj 2007). Operations can be severely disrupted, come to a complete halt or deliveries can be delayed if such risks are not proactively planned for, ultimately leading to a domino or ripple effect (Ivanov et al. 2018; Kinra et al. 2020), propagating and affecting subsequent operations in the wider SC network and hence its resilience, as SCs are as strong as their weakest supporting links. Examples of such effects could be seen in the 6-day interruption of the Suez Canal by the container ship *Ever Given* in March 2021 (Özkanlısoy and Akkartal 2022) or the 50-day blockage of the Rhein-Railway at Rastatt in July 2017 (Borghetti and Marchionni 2023).

Risk management thus plays a pivotal role in building the resilience of an organization (Martin and Peck 2004), which is defined as the 'ability of organizations to return to its original state or move to a new, more desirable state after being disturbed' (p.4). This ability to return to original or new states after the disturbance, largely depends on whether the organization(s) was able to proactively make decisions before the disruptive event took place rather than during or after the event (Murino et al. 2011) (reactive responses). Risk management includes several steps such as risk identification, risk assessment and risk mitigation (Collier et al. 2022; Madni and Jackson 2009; Sodhi et al. 2012). However, 'risk prioritization' has also

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been deemed to be an important step (Elangovan et al. 2021; Faisal 2009), especially in the current Industry 4.0 (I4.0) environment (Pandey et al. 2021). Simulation modeling is a common method to analyze and quantify risks that impact a SC (Finke et al. 2010; Flammini 2021). Such models can help industrial practitioners manage their operations based on the priority of risk impacts and hence build the resilience of their organizations as well as their SCs.

Ongoing development of new and more sophisticated products continue to demand more components which can only be provided by specialized suppliers. In addition, continued drive for globalization distributes SCs over larger areas, in more countries and on multiple continents. This development poses several challenges to managing risks (Pearsall 2016) such as:

- Elongated SCs, with many parts sourced from sub-tier suppliers.
- Less visibility of data related to critical parts, delivery times, etc. due to sub-tier sourcing.
- Presence of components and suppliers in multiple countries.
- Longer distances between means of production.

In addition to the above challenges, SCs are growing at a scale that is difficult to oversee and manage manually by humans, making it harder for SCs to prioritize and manage risks that have different degrees of impact on their operations. In view of these challenges, the question we hence try to address in this paper is: How can we prioritize risks for building the resilience of manufacturing supply chains?

Artificial intelligence (AI) powered solutions can help to identify risks; however, a multitude of requirements need to be met for successful deployment (Alzahrani and Asghar 2023). We took on the task of an iterative journey to implement an AI solution first by generating synthetic data of an SC for AI model exploration. We analyzed a SC in the Digitala Stambanan project (Digitala Stambanan 2021) which primarily consisted of three companies (hereafter companies 0, 1, 2 and 3). Here, value is created through specific customized processes and activities starting from the flow of raw materials from companies 0 (sheet metal provider) and 1 (provider of nuts and bolts) to company 2 (where the assembly of steel products takes place) which delivers the finished product to the end customer, which is the OEM (3). The SC partners collectively agreed that the timely delivery of products (delivery assurance) was the primary objective for value creation in the SC. As delivery assurance is a subjective concept, we focused on throughput as the measurable value at this stage of development. However, there are various reservations among partners to share data and implement AI such as data security and lack of trust in AI. Therefore, we attempt to circumvent this challenge by developing a modelling approach based on discrete event simulation (DES) which can simulate the goods flow in a SC. The present simulation model quantifies the impact of pre-defined risks (with a range of likelihood and impact) on the throughput of the SC which could then help companies prioritize the risks. The data produced by the simulation model can be used at a later stage for the demonstration of a throughput prediction model based on synthetic data to demonstrate the capabilities and benefits of an AI system. The model serves the only purpose of accelerating the development process of an AI system. Validation will take place only later and will be applied directly to the AI system trained on real data.

Following this introduction, the rest of the paper is organized as follows. Section 2 presents the frame of reference, Section 3 discusses the overall method and modeling approach for prioritizing risks, Section 4 presents the results in the form of experiments and we end the paper with conclusions and future work in Section 5.

2 FRAME OF REFERENCE

2.1 Supply Chain Risk Management and Resilience

Resilience can be defined as '*a measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables'* (Holling 1973) (p.14). For the case of a SC, the responsiveness of companies to the different shocks between nodes or arcs in the SC can be associated to its 'resilience' and hence of the entire SC, which can then be attributed to its competitive position in the market (Sheffi and Rice 2005). Hence, companies must be able to respond to such unintended events and quickly return to pre-disruption levels or even better states of performance, while maintaining consistent output levels. We consider disruptions to be interruptions in operations that are caused by various risks impacting the SC.

Sheffi and Rice (2005) describe a company's response to disruptions and the corresponding impact on its performance in the form of eight phases as follows (Figure 1): The first step is preparation which entails proactively foreseeing possible disruptions that could occur and minimizing its impacts. When the disruption occurs, the next step is a reactive response that aims to control the situation and prevent it from creating more damage to operations. Although the magnitude of the initial impact could be less at the beginning, it could take time to propagate and for the full extent of the damage to be seen. When this occurs (either immediately or with a delay), firms must then prepare to recover from the impacts of the disruption. Recovery activities then try to bring back operations to normal levels after which the long-term impacts must be carefully considered for future strategy planning for risk and disruption mitigation.

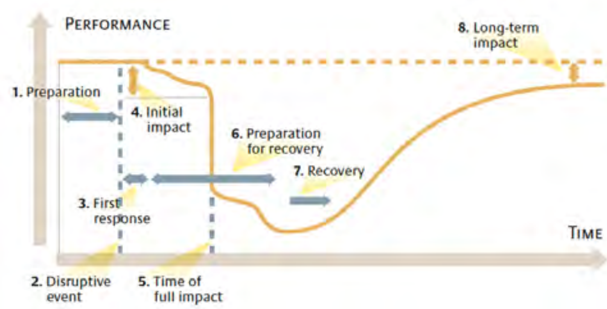

Figure 1: Disruption profile characteristics (Sheffi and Rice 2005).

Risk, as defined in the risk theory domain, 'is a situation or event where something of human value (including humans themselves) is at stake and where the outcome is uncertain' (Birkie et al. 2014) (p.84). That is, risk is perceived to exist when there is a large likelihood that the unintended event and corresponding disruption that occurs has a significant impact or cost associated with them (Faisal 2009). Risks have had several typologies associated with them in SC and Supply Chain Risk Management (SCRM) literature. Some have been categorized based on the location of risks: internal and external risks (Martin and Peck 2004) while some others on the impact of risks: operational (e.g., from uncertain demand and supply) and disruption risks (e.g. earthquakes, natural disasters and geo-political issues) (Tang 2006). Others such as Ivanov et al. (2017) categorized disruption risks at the SC level according to production, supply and transportation risks.

As previously described, risk management also entails several stages or steps namely risk identification, risk assessment, risk prioritization and risk mitigation (Elangovan et al. 2021; Faisal 2009; Madni and Jackson 2009). Risks could also have dependencies and inter-relatedness that may have an impact on one or more organizations in the SC (Murino et al. 2011), destabilizing the whole system. We have considered these aspects while modeling risks in the present study.

2.2 Simulation Modeling and Artificial Intelligence

Although the overall deep learning architecture for supply chain risk is not yet fully solved, supply chain risk prediction is an emerging field which deserves attention because of the vast potential of cognitive perception of artificial intelligence-based solutions. However, deep learning-based solutions depend on available data for model exploration and testing (Alzahrani and Asghar 2023).

Many partners are often reluctant to share data due to a variety of reasons, which is also the case in this study. To circumvent this problem, methods based on generative AI were already proposed to generate synthetic data which approximate the data featured in a problem (Panfilo et al. 2023). Access to real data is also required with generative AI, or SC partners need competent personnel who are familiar with AI inhouse who can apply similar methods as proposed by Panfilo et al. (2023). However, this is not the case in the present study. Synthetic data from modelled data can be used for various computer vision (CV) applications and also for other forms of data problems (Nikolenko 2019). We aimed at using this concept to approximate the data featured in goods flow of a SC synthetically, using a DES modelling approach. A framework was proposed to use DES for synthetic data generation for a manufacturing system in a single plant (Chan et al. 2022). We aim at using this method, but apply it to represent a whole SC.

3 METHOD

The objective of this study is to develop a digital model of a supply chain (SC) that is affected by determined risk events. The SC model centers around two critical components that are responsible for producing or transporting goods. These risk events temporarily reduce the production or transportation capacity of the selected SC elements, resulting in disruptions that diminish the output of affected components. Because of the nature of SC, elements deliver goods to other elements, and disruptions can propagate and cause disruptions in other unaffected elements which are in lower tiers. We decided to approach this challenge and propose a model which approximates the physical SC system, however, without any real-time data transfer, and using a simplification of bottlenecks theory in serial production (Tu et al. 2021) to represent goods flow in a SC.

3.1 SC Modeling Approach

The numerical DES approach (Fujimoto 1990) was developed as a proof-of-concept demonstrator to simulate flows and identify the consequences of each risk. We worked with our SC partners who gave us a basic representation of the SC and defined its risks qualitatively.

Given the scarcity of available data, we were compelled to define the fundamental characteristics that represent the risks and make certain assumptions regarding the flow of goods. As a result, we developed a basic model that relies on two primary elements: 'nodes' that produce goods and 'arcs' that transport goods from one node to another. The SC is built as a directed graph, with each node responsible for producing a single product. The highest tier nodes do not require products as input, but the other nodes require an input to be able to produce an output. The model is implemented in python making extensive use of the pytorch library (Paszke et al. 2019).

To build the demonstrator we replicated a real SC that consists of four companies 0, 1, 2 and 3 (OEM), all of which are based in Sweden. The risks description, SC architecture, product and information flow is presented in Figure 2. Data was collected from the SC partners through two workshops conducted in January and March 2023 along with interviews with top-level management at the companies.

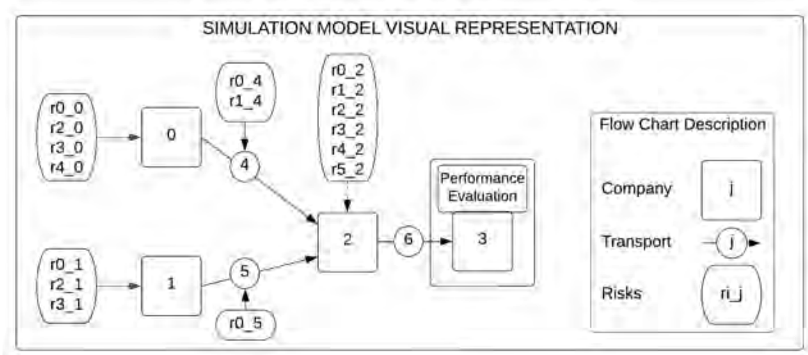

Figure 2: SC simulation model visual representation.

A node n_j has an input buffer $\boldsymbol{b}_{in,\ j} \in \mathbb{N}^n$ and an output buffer $\boldsymbol{b}_{out,\ j} \in \mathbb{N}^n$ where raw materials and finished products are stored. Each product has an assigned vector $\boldsymbol{d}_{raw,\ j} \in \mathbb{N}^n$ which defines how many products a node needs, with pre-products to produce one unit of its output products. A node also has a capacity to produce goods $\beta_i \in [0,1], \beta_i \in \mathbb{R}$. Arcs a_i transport one type of goods from one node to the next. Analogue to nodes, they have a capacity to transport $\gamma_i \in [0,1], \gamma_i \in \mathbb{R}$ but no buffers. Nodes produce goods in each timestep $\boldsymbol{p}_{real} = (\boldsymbol{\beta} * \boldsymbol{p}_{max}),\ \boldsymbol{p}_{max} \in \mathbb{N}^n$. Nodes and arcs are also exposed to risks which are defined by the parameters explained below.

3.2 Risks Representation and Disruption Function

Risks can occur in each time-step randomly and each node and arc can be exposed to multiple risks, except the last element of the SC where we assume undisrupted production. We decided to replicate a risk event by defining three parameters:

1. Probability: $P(r)$
2. Capacity impact: $c_r \in \mathbb{R} \mid c_r \in [0, 1]$
3. Time interval to fix the disruption: $\tau_r \in \mathbb{N}$

As shown in Figure 3, a risk event causes a disruption of the production capacity resulting in a temporary bottleneck. In the case of an event happening, the capacity of a node or transport arc is temporarily reduced. The new capacity of a node or arc is given by: $\tilde{\beta}_i = \beta_i * (1 - c_r)$, or $\tilde{\gamma}_i = \gamma_i * (1 - c_r)$ respectively. The effect of a risk event triggering a disruption is displayed in Figure 3. Companies can be exposed to multiple risks which could trigger risk events at the same time. For our present case, we made the following assumption: The system is always defined by the weakest link and therefore the total capacity of production is the value of the lowest element. This is a simplified concept based on a bottleneck in serial production. (Tu et al. 2018) Thus, the total capacity is the minimum value of all these simultaneous disruptions $\tilde{\beta}_i = min(\tilde{\beta}_i{}^k)$ for nodes or $\tilde{\gamma}_i = min(\tilde{\gamma}_i{}^k)$ for an arc.

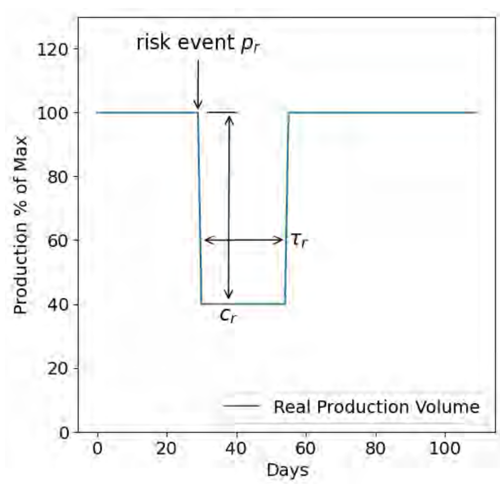

Figure 3: Risk event and disruption effect on production or transport capacity.

3.3 OEM Performance Evaluation Strategy

With our DES model in place, we were able to simulate the flow of goods and identify the consequences of each risk event. Through this model, we performed a risk quantification analysis that enabled us to evaluate the impact of different risks on the SC. The definition of risks' fundamental characteristics and flow of goods simplification (Tu et al. 2021) enables the basic model development. The location of the evaluation takes place at the OEM production node 3 where we compare $a, b \in \mathbb{N}$, where a is the ideal production (max capacity) and b the real production. Additionally, we have $a \geq b$. But, to provide insights into the vulnerabilities of the SC we need to define evaluation functions to the OEM. To evaluate the performance, we defined four different evaluation functions (1) – (4):

$$f_0(a,b) = \frac{a-b}{b} \tag{1}$$

$$f_1(a,b) = \begin{cases} 1, & \text{if } a = b \\ 0, & \text{if } a \neq b \end{cases} \tag{2}$$

$$f_2(a,b) = 1 - \left(\frac{a-b}{b}\right)^2 \tag{3}$$

$$f_3(a,b) = \begin{cases} 1, & \text{if } a = b \\ \frac{1}{2}\left(1 - \frac{a-b}{b}\right), & \text{if } a \neq b \end{cases} \tag{4}$$

These evaluation functions were chosen to study the effect of different common evaluation functions. (1) representing the absolute error, (2) representing an indicator function, (3) mean square error and (4) a hybrid between absolute and indicator function. Through simulation of various risk scenarios, our model enables the identification of potential failure points in the supply chain and evaluation of risk mitigation strategies. This approach facilitates the development of contingency plans to minimize disruptions and ensure optimal performance of the manufacturing supply chain.

4 EXPERIMENTS

The output of this analysis is a risk prioritization where the risks are ranked according to their impact on the capacity to deliver by the focal company i.e., the risks are ranked according to their impact on loss. Using this model for risk prioritization enables generating scenarios with different sets of risks and shows the potential of developing corresponding mitigation strategies with respect to these risks at the focal company.

4.1 Demonstrator Model Implementation with Qualitatively Collected Risk Parameters

We engaged with industry stakeholders to gain a comprehensive understanding of the risks that are most relevant to the specific supply chain under consideration. Our approach to risk characterization was therefore empirical, drawing on the insights and expertise of those who are intimately familiar with the day-to-day operations of the supply chain. Figure 4 provides a visual representation of the qualitative measures used to characterize the risks r_0, r_1, r_2, r_3, r_4 *and* r_5 in the manufacturing supply chain model. In Figure 2 it was visible which nodes of our SC are exposed to which instance of these risks. Taken together, these qualitative measures provide a useful framework for understanding and characterizing the various risks facing a manufacturing supply chain.

Six risks (r_i) were identified in the SC and what they all have in common is that they temporarily slow down the production capacity:

- r_0*, data missing (operational):* Delivery data about critical parts are unknown; different data formats from suppliers who have different systems; material received but with wrong part numbers; critical dimensions of item not supplied by customer; no insight about the item's environment, how it will be assembled and its criticality in the process functions),

- r_1, *deviations in material characteristics unknown (operational):* Steel is not of a required specification or not completely flat; material surface defects; material received is in outer tolerance range; flatness of material cannot be 'seen'),
- r_2, *unique material specifications (demand-side):* of company C (thickness and grade of steel that is not common and required by the OEM; material coming from a specific steel mill),
- r_3, *machine/furnace breakdowns (system):* When a machine or furnace breaks down, it can cause significant delays and downtime, which can impact the timely delivery of finished goods.
- r_4, *dependency on suppliers (supply-side):* Who provide material with unique specifications and from specific mills. also shows where the risks occur in the SC (which companies and arcs or transactional paths between companies are impacted). We assume that no risks occur at the OEM but only how the risks in the upstream SC activities can have an impact on its performance.
- r_5, *cyber-security and data breach risks (cyber):* A cyber-attack or data breach can have serious consequences for a manufacturing supply chain, leading to the loss or theft of sensitive information, such as proprietary technology or customer data, causing disruptions to operations.

By characterizing these risks at a higher level of detail, we can understand the potential vulnerabilities of the supply chain. This information is crucial for designing effective risk management strategies that can help mitigate the impact of disruptions and maintain the resilience of the supply chain.

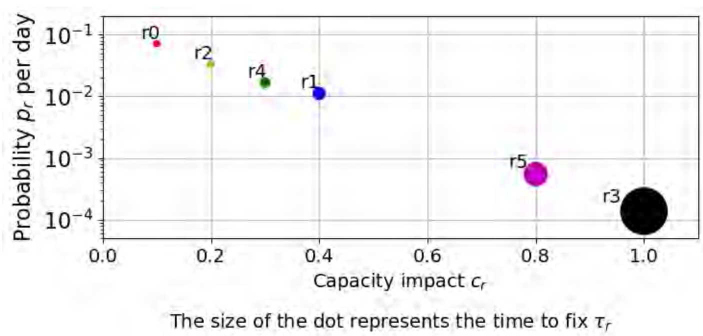

Figure 4: Experiment set up with identified risks and associated parameters which were defined in equation 2. The risk impact with respect to the parameters can be observed in Figure 3. In Figure 2, it is visible which node is exposed to which instance of these risks.

4.2 Generated Production Rates in the SC

In the first experiment we investigated the production of each node 0, 1, 2 and 3. Nodes 0-2 are exposed to risks which lower the production capacity of each producing node and transporting arc. We have simulated the goods flow of the introduced SC for 1'000 days, and 10'000 parallel random results were generated. This represents a simulated total timeframe of approximately 30'000 years.

In Figure 5, goods produced in each node are displayed for different sets of samples from the previously mentioned results. We note low differences in production of each node in the *100th* (a) and the *50th* (b) *percentile,* however in the *10th* (c) and *1st* (d) we observe two groups - nodes 0 and 1, and nodes 2 and 3 whose current production capacity is close to one another. We see that node 3 trails node 2 most of the time in (c) and (d). This behavior cannot be a consequence due to disruptions caused by risks at node 3 because this node is not exposed to any risks. Therefore, lower production values are observed at node 3 which are caused by disruptions at previous supplier nodes as this node depends on having adequate supplies for a smooth production to take place. As nodes 0 and 1 have higher production values at all times compared to nodes 2 and 3, the behavior for lower production at node 3 needs to be caused by events at node 2.

The production of node 3 is only lowered if raw materials from node 2 are missing. This behavior could therefore indicate that node 2 represents a bottleneck which sometimes fails to adequately supply node 3.

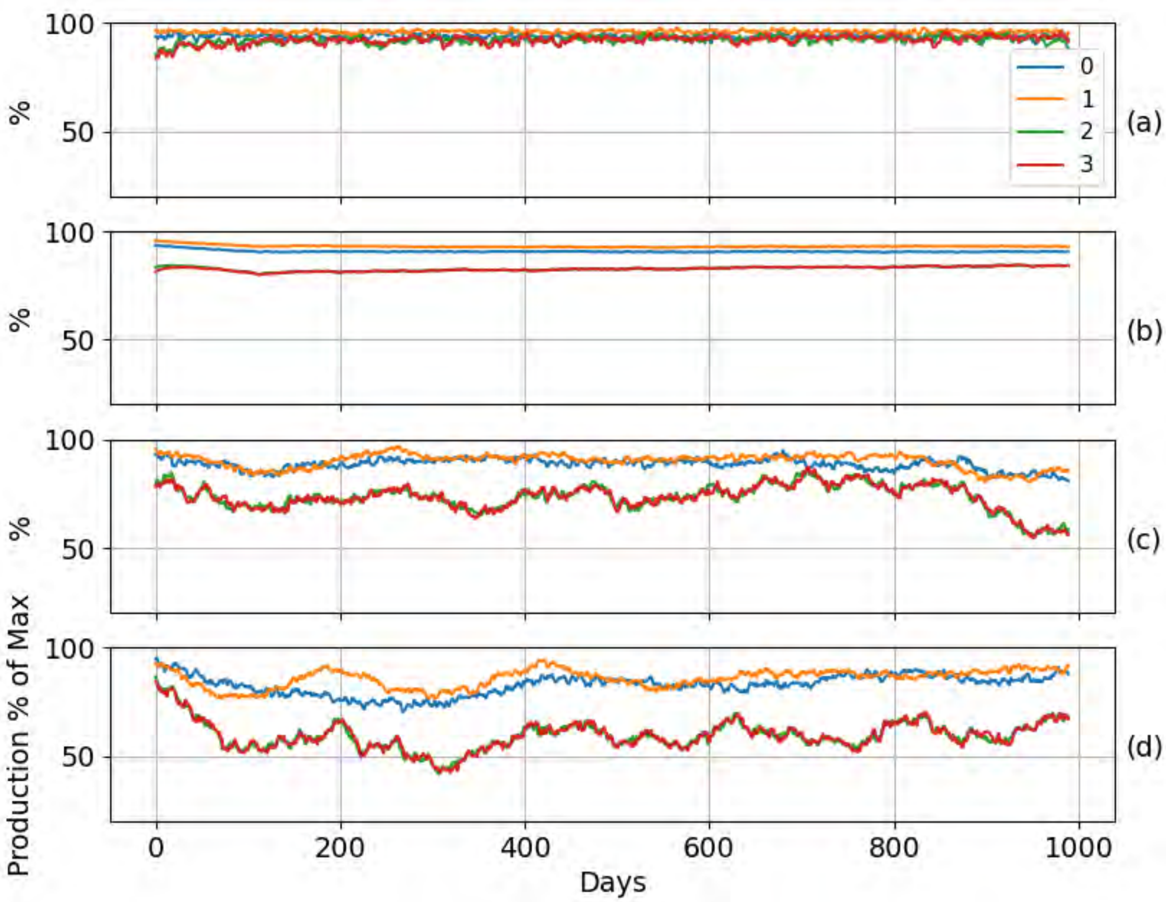

Figure 5: Daily production of node 0 (blue), 1 (orange), 2 (green) and 3 (red). 10’000 samples of 1000 days were simulated. The average performance of percentile 100th (a), 50th (b) 10th (c) and 1st (d) are displayed. Node 0-2 are exposed to risks which can disrupt the production. The production of node 3 is only lowered if components of the supplying node 2 are missing.

4.3 Single Risk Impact Evaluation

We now estimate the impact of each instance of risks on the SC introduced in 3.1 (observable in Figure 2) and at the beginning of this chapter with respect to the overall performance of the SC. To evaluate the performance, we make use of the previously defined evaluation functions (1) – (4). The location of the evaluation takes place at the OEM production node 3. In order to evaluate the overall impact of each instance of risk $r_{i,j}$ we lowered the probability $p_{r_{i,j}}$ of each risk separately while leaving all others at the defined level.

For each $k \in \{0, ..., 9\}$ defining a parameter $\lambda_k = 0.1 * k$ we obtain the new probability $\tilde{p}_{r_{i,j},k} = \lambda_k * p_{r_{i,j},k}$We note that in the case of $k = 0$, the probability $\tilde{p}_{r_{i,j},k}$ will become 0 and in this case eliminating the risk. For each $\tilde{p}_{r_{i,j},k}$ we have run the simulation for 10’000 time-steps, and we generated 100’000 different random parallel scenarios for evaluation. The average improvement over the baseline scenario was taken as a measure to evaluate the impact.

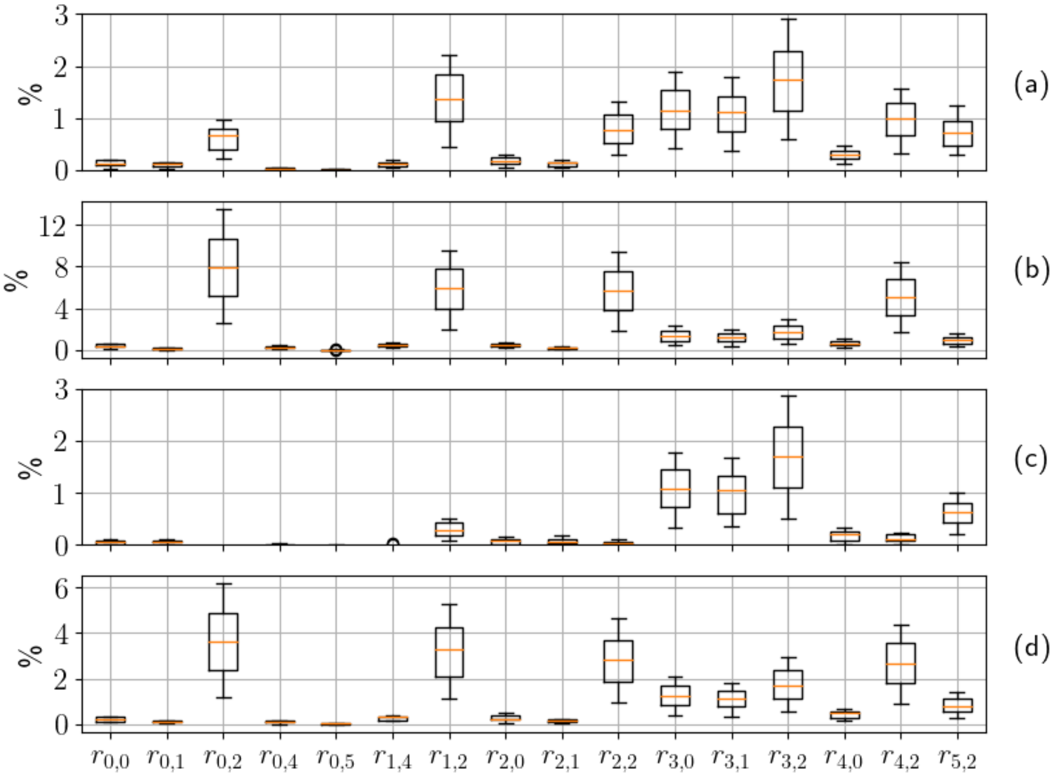

Figure 6: Risk impact analysis for each instance of risks evaluated with function defined in (Equation 1) (a), (Equation 2) (b), (Equation 3) (c) and (Equation 4) (d). The same could also be observed in Figure 2, where it was shown how these risks can disrupt the goods flow in the SC. We lowered the probability for each instance of risk while maintaining the probability of all other risks. The lower end of each bar represents the $k = 9$ and the upper $k = 0$, eliminating this risk $\tilde{p}_{r_{i,j},k} = 0$.

In Figure 6, the result of our evaluation for each risk instance is visible. We can observe that some risk instances have a larger impact on the SC as others regardless of the evaluation function. We also see that the result depends on which evaluation function Equations (1) – (4) we are using. Different instances will be evaluated with a large or low impact. For example, $r_{1,2}$ has a higher impact in all evaluation functions except (Equation 3). $r_{0,2}$ has according to (Equation 2) a very high impact, but according to (Equation 3) a negligible one.

These differences show that defining the evaluation function is a key component in defining an evaluation metric for SC performance analysis. The nature of (Equation 1) and (Equation 3) penalize especially high probability; relative impact in the case of (Equation 1) has no effect and a comparatively low one in (Equation 3). On the other hand, we have (Equation 2) and (Equation 4) where especially (Equation 2) favors high production values but does not penalize low impact disruptions much. It is not surprising that in this regard, according to (Equation 2) (the high impact low probability) three instances of $r_{3,j}$ are the most disrupting risks to the SC. All results have in common, that is, in case of (Equation 1) the top two, (Equation 2) top five, (Equation 3) the first and (Equation 4) again, the top five most disruptive risks identified are all associated with node number 2. All the functions in this regard also point towards building more resilience in node 2 first.

4.4 Limitations

The verification and validation of the simulation model was performed only qualitatively in collaboration with our SC partners. We conducted *face validity* (Sargent 2010) and created *operational graphics* for validation of the model due to the nature of the conceptual state of the model. Values of the output parameters (here, performance of the SC in terms of throughput and lead time) were graphically shown through the various timesteps to check if the model behaved as intended. For the next iteration, however, suitable quantitative means of verification and validation need to be investigated.

5 CONCLUSIONS AND FUTURE WORK

The present study provides a DES model which is a proof-of-concept to showcase the capability of visualizing and prioritizing risks along a manufacturing SC. The need for such a study is grounded in the fact that different data sources are available at the SC partners, the requirement of visualisation and prioritisation of risks holistically, showcase which company is the critical bottleneck in the SC, and build trust for future more sophisticated systems. DES modeling was deemed to be the best approach for this study, as it allows flexibility in testing multiple complex risks while evaluating the trade-offs for prioritization of high impact risks and the corresponding development of mitigation strategies. If the estimation of risks identified qualitatively are accurate, it would point to building more resilience in company 2, i.e., this assumption can be fulfilled only if the qualitative risks identified, accurately represent reality. As part of the digital transformation process in I4.0 (according to the I4.0 Maturity Index (Schuh et al. 2020)) of SCs, the implementation of our simulation model is the first stage (visibility) in this process that enables a digital SC risk assessment and prioritization.

The capabilities of simulation models and the usefulness of establishing experience with digital risk evaluation are many: (i) quantify impact of risks so that prioritization can take place. Even though the quantified data is not perfect, it can give a justified assessment where several scenarios can be established with different sets of risks and the results of each can be compared, and, at later development stages, having already an approximative digital representation of the real system, the model can be used to develop more sophisticated mitigation strategies to address the impact of risks on the capacity to deliver; (ii) develop proactive mitigation strategies. Risks are inherently part of the different links and nodes of SCs, and it is not possible to completely avoid them (Faisal 2009). Hence, it is important that organizations establish in the early stages what risks could impact their operations as well as their SC partners. Further, with a thorough understanding of the different risks and how to prioritize them using simulation models, actors in a SC can proactively create mitigation strategies and plan their resources more efficiently; (iii) generate synthetic data (Rengkung 2018) to train a deep neural network which could be used to automatically detect the most problematic node or arc. Random risks could be generated for a given SC and the storage time series stored as input data. The trained network could also be evaluated towards real data and with Turing tests (Schruben 1980); (iv) the model could be expanded to include delays in deliveries of arcs which at this iteration was not included. Real data could be (partially) included in the model to improve the representation; (v) a possibility of future integration into Digital Twins whose corresponding capabilities can help manufacturing organizations further build its resilience (Maheshwari et al. 2022).

Bonini's paradox explains the difficulty in creating models and simulations that fully represent complex systems and as such, the more 'complete' they are, the less understandable and useful they become. Applying the paradox in this paper, we tried to find a balance between usefulness and accuracy in the modeling of the simplistic SC chosen, and attempted to model its flows such that it represents reality in a reasonably good manner. With increasing pressure for SCs to be more efficient from a sustainability point of view (Reyes et al. 2023), they may need to incorporate resilience and risk management strategies if they want to improve their sustainability performance (Zavala-Alcívar et al. 2020).

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